Current Psychology (2024) 43:30379–30401
https://doi.org/10.1007/s12144-024-06649-3

Harnessing AI potential in E-Commerce: improving user engagement and sales through deep learning-based product recommendations

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Accepted: 2 September 2024 / Published online: 10 September 2024

Abstract
Artificial intelligence (AI) has become a game-changing influence in e-commerce, reshaping the way businesses interact with customers and increasing operational efficiency. In today's digital era, AI technologies are being progressively embedded into e-commerce platforms to enhance the user experience, improve processes, and drive business growth. One of the primary areas where AI demonstrates its potential is in personalized product recommendations. This study explores the development of AI-driven recommendations regarding product design, sales, and customer experience in e-commerce environments. The research employs a quantitative approach to explore how AI technologies can enhance various facets of online retail. Using purposive sampling, 439 consumers and 356 sellers from diverse regions of China participated in an online survey designed to gather insights into their interactions with AI-driven recommendations. Data analysis was rigorously conducted using Lisrel 10.20 and Smart PLS 3 software, focusing on validating hypotheses related to AI's influence on consumer behavior and business outcomes. Key findings include AI's significant role in boosting productivity, enhancing sales figures, and enriching consumer experiences through personalized recommendations. This research provides a deeper insight into AI's potential in e-commerce and provides recommendations for businesses focused on using AI technology to increase user engagement and increase sales in digital marketing.

Keywords AI-driven product recommendation · Personalized consumer experience · E-commerce sales optimization · Digital marketing strategies

Introduction

The rapid development of artificial intelligence (AI) has introduced revolutionary adjustments in many fields, including e-commerce, by offering unprecedented opportunities to enhance consumer engagement and optimize business operations (Khrais, 2020). In the realm of e-commerce shopping, AI-driven product recommendations have become a crucial tool for businesses to personalize user experiences, increase sales, and improve overall customer satisfaction (Zhang, 2024). These recommendations leverage deep learning algorithms to process vast amounts of data and forecast customer preferences with high accuracy. The primary motivation behind this study is to empirically investigate how AI-driven product recommendations influence key metrics in e-commerce, namely productivity, sales performance, and consumer experience. As consumer behaviors evolve and digital interactions become more personalized, understanding the influence of AI on these changes is of great importance for businesses that want to be competitive in the digital economy (Bag et al., 2022; Musiolik et al., 2024). This study seeks to understand the effectiveness of AI technology in increasing user interaction, optimizing sales strategies, and tailoring shopping experiences based on demographic factors like age and income.

However, amidst the growing adoption of AI in e-commerce, several critical gaps remain in understanding its specific impacts and potential applications. There is a need to empirically evaluate how AI-driven product recommendations enhance productivity, boost sales performance, and improve overall consumer experiences. This gap underscores the importance of validating the effectiveness of AI

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technologies in achieving these strategic objectives within diverse e-commerce contexts. The varying impact of AI recommendations across different demographic segments, such as age and income, remains underexplored. Understanding how consumer behaviors and preferences differ across these demographics is crucial for tailoring AI recommendations effectively and enhancing user engagement. This study seeks to address these gaps by investigating the evolution of information in e-commerce, emphasizing its effect on user experience, particularly emphasizing its effect on user engagement, sales enhancement, and consumer experience. By addressing these research gaps, this research seeks to provide empirical insights that contribute to both theoretical advancements and practical applications in harnessing AI to optimize digital commerce strategies.

This study used multiple methods and structural equation modeling (SEM) assessment to gauge the effect of product intelligence-based recommendations on productivity, sales, and customer experience. Purposive sampling and data collection through an online questionnaire from 439 consumers and 356 sellers across diverse regions of China known for significant e-commerce activities ensure a targeted and insightful dataset. The rigorous analysis using LISREL 10.20 and Smart PLS 3 software enhances the robustness of statistical evaluations and validates the suggested hypotheses. The main outcome of this examination provides a clearer understanding of how intelligence affects consumer behavior and business outcomes in e-commerce. SEM is used to evaluate the direct and indirect impacts of AI-driven recommendations by examining relationships between insights and variables. In SEM, confirmatory factor analysis (CFA) ensures the reliability and validity of the measurement model, while simultaneous analysis allows multiple relationships to be evaluated simultaneously. The significance of this study is rooted in its potential to inform e-commerce stakeholders, including businesses, policymakers, and researchers, about the strategic implications of AI adoption. By elucidating how AI enhances productivity, boosts sales, and improves consumer experiences, this research contributes to optimizing digital commerce strategies. Businesses can gain insights into tailoring AI-driven recommendations to meet diverse consumer needs effectively, thereby enhancing engagement and satisfaction. Policymakers can use findings to shape regulations that foster responsible AI deployment, addressing ethical considerations and ensuring consumer trust.

Contributions and novelty

- Examining the transformative impact of harnessing AI potential in e-commerce through advanced product recommendation systems.
- Investigating how consumer experience in e-commerce is influenced by both the age and income of consumers.
- Exploring how product recommendations in e-commerce enrich consumer choices and options, as well as enhance personalized shopping experiences.
- Analyzing how AI enhances product recommendation systems.
- The uniqueness of this research stems from its thorough approach to the search for AI's potential in e-commerce, from enhancing productivity and sales to improving consumer experience through personalized recommendations.

Research objectives

RO1 To examine the effects of AI-driven product recommendations on productivity and for working within the e-commerce sector.

RO2 To discover the impact of intelligence-focused product recommendations on productivity and revenue generation for businesses operating in the e-commerce industry.

RO3 To explore the connection between AI-driven product recommendations and consumer experience in online shopping contexts.

This article continues with a literature review in Sect. 2, followed by the study's conceptual framework in Sect. 3. Section 4 details the methodology, while Sect. 5 presents the results. A comprehensive discussion, including theoretical and practical implications, is provided in Sect. 6. The article concludes in Sect. 7, addressing limitations and suggesting avenues for future research.

Literature review

AI-enhanced consumer engagement strategies

Misra et al. (2024) studied how AI algorithms affect how people make decisions when shopping online. The investigation discovered that consumers are most affected when algorithms have moderate levels of control. This highlights the need for personalized AI designs and empowering users to feel in control of their purchases. The study suggested that achieving a balance between AI and human interaction is essential for improving how engaged and satisfied customers are when shopping online. Asante et al. (2023) aimed to explore how AI elements in e-commerce platforms and customer involvement extend beyond purchase intentions, and factors like chatbot performance, picture search capabilities, recommendation system effectiveness, and automated post-sales care are significant drivers of this. Using the S-O-R paradigm and PLS-SEM analysis on 464 survey responses, the research found that these AI capabilities enhance consumer engagement behaviors. Attention to social comparison was found to moderate these effects, weakening the impact of chatbots and after-sales service but strengthening the effect of recommendation systems. Sheshadri et al. (2024) examined how incorporating AI into marketing management could improve customer engagement. The study explores AI technologies by using a mixed-methods approach that combines literature reviews, case studies, surveys, interviews, and data analytics. The findings revealed that AI significantly improves consumer engagement through personalized marketing messages, promotions, and product recommendations. The report also discusses consumer trust, data privacy, and algorithmic biases as ethical concerns. Dudzinskaite et al. (2024) examined the potential for increasing consumer engagement in digital marketing campaigns through the use of AI-enhanced methods. Ten semi-structured interviews with prospective clients, split into two age groups (20–30 and 40–50), were done using a qualitative method. The results demonstrated how users' propensity to interact with digital ads was influenced by factors such as informativeness, aesthetically pleasing design, tailored content, relevancy, and clear language, all of which greatly improved engagement. Tula et al. (2024) found that while AI is transforming customer experience by enabling personalization, automation, and predictive analytics, businesses must strategically integrate AI to overcome obstacles and promote sustainable growth by prioritizing ethics and working together across functional boundaries.

Technological innovations in recommender systems

Ko et al. (2022) explored the close connection between the technical advancements in recommendation systems and their business applications across diverse service areas. By analyzing over 135 top-ranked articles and conference papers published from 2010 to 2021, the study found that the growth and development of recommendation system research are closely linked to the business growth of the applied service fields, revealing the immense potential of these systems to drive innovation and growth across various industries. Javed et al. (2021) investigated two essential recommendation systems. The first is a context-aware system that applies filters to objects according to the location and time of the user. The second is a context-based system that recommends items by analyzing patterns from users' past interactions on the web. Methods including collaborative filtering, content-based filtering, and semantic reasoning with RDF (Resource Description Framework) and OWL (Web ontology language) were used. The exploration sought to improve smartphone media suggestions, sift through e-learning materials, and provide tailored news. The research mentions that these systems effectively customize recommendations based on user interests, resulting in improved user engagement across various applications. Jesse and Jannach (2021) explored integrating digital nudging mechanisms into recommendation systems to guide user decision-making. Through a systematic review, 87 nudging mechanisms were categorized, revealing the potential for enhancing recommender systems by strategically applying these nudges to optimize user interaction and content engagement online. Tran et al. (2021) examined recommended situations such as food, drug, health status prediction, healthcare service, and healthcare professional recommendations to improve decision-making for users and medical professionals. The study methodically assessed the literature on healthcare recommender systems. The finding of the study indicated that healthcare recommender systems have the potential to significantly enhance decision-making by integrating diverse recommendation scenarios and improving accuracy in healthcare recommendations through the use of complex data sources. Ferrari et al. (2021) aimed to evaluate how well deep learning-based neural techniques improve recommender systems by comparing them with simpler baseline methods. It used consistent evaluation metrics to analyze recent neural approaches in collaborative filtering against established techniques such as nearest-neighbor heuristics and linear models. The results showed that 11 out of 12 reproducible neural methods consistently performed worse than these simpler approaches. This challenges the common assumption about deep learning's superiority in recommender systems and suggests that current research practices may be stagnant, prompting a need to reassess methodologies to drive real progress within the domain.

Impact of AI on E-commerce performance

Chen et al. (2022) investigated how AI capability (AIC) in E-Commerce firms, analyzed through the higher-order model, impacts business performance through AI-driven decision-making, management techniques (AIM), and creativity (AIDDM). Based on 394 questionnaires and partial least squares structural equation modeling (PLS-SEM), it was found that AIC greatly improves business performance by influencing these variables. The study emphasized how environmental dynamism has a mediating influence and innovation culture has a moderating role. Fonseka et al. (2022) sought to investigate how Sri Lankan SMEs' business performance was affected by the use of e-commerce, with a specific focus on how AI moderates this relationship. Using data from 389 senior managers, the study discovered that using AI and e-commerce together greatly improves business success. Furthermore, it revealed that managerial demographics, such as age, gender, education level, and job position, influence managers' perceptions of these technological impacts. Bawack et al. (2022) synthesized existing bibliometric analysis and a literature review are used in AI research in e-commerce, with an emphasis on recommender systems, sentiment analysis, trust, personalization, and optimization. It highlighted China's leadership in this field and proposed future research directions for enhancing AI's role in e-commerce. Areiqat et al. (2021) explored how AI has revolutionized e-commerce by enhancing customer interactions through chatbots, personalized services, and predictive analytics. It emphasizes how important AI is to determining how online retail will develop in the future, where a significant shift towards AI-managed customer interactions is anticipated. von Zahn et al. (2022) investigated AI fairness in e-commerce, focusing on equitable coupon allocation based on clickstream data. By integrating fairness constraints into AI algorithms, the examination aimed to address disparate outcomes related to sensitive attributes like gender and age. The methodology involved applying these fairness techniques to a real-world use case and evaluating their impact on prediction performance and financial costs. Findings revealed that while AI fairness successfully ensured equitable outcomes with minimal reduction in prediction accuracy, it also resulted in increased financial costs, highlighting the trade-offs between fairness and economic considerations in AI-driven information systems.

Personalization strategies

Gupta et al. (2020) aimed to advance the understanding of deep learning-based recommendation systems by presenting real-world, production-scale deep neural networks for personalized content ranking and relevant performance metrics. The methodology involved releasing open-source workloads and conducting an in-depth analysis of these workloads. Key findings included a 60% variation in inference latency across three Intel server generations, significant improvements in latency-bounded throughput through batching and co-location of inference jobs, and the need for diverse optimization strategies due to the diversity in recommendation models. Cui et al. (2020) introduced TCCF, a novel recommendation model designed for IoT environments, which utilized time correlation coefficients and an enhanced clustering method (CSK-means) to cluster similar users effectively and improve recommendation accuracy. Additionally, PTCCF further enhanced recommendation quality by analyzing user behavior patterns. Experimental validation conducted on MovieLens and Douban datasets demonstrated that TCCF and PTCCF models increased recommendation precision by 5.2% compared to traditional methods, confirming their effectiveness in dynamic IoT settings. Yuan et al. (2020) aimed to enhance recommendation algorithms using ACA-GRU, a context-aware, attention-based model using a Gated Recurrent Unit (GRU). It categorized and integrated four types of context information to model user interest dynamics more accurately. Experimental results showed ACA-GRU outperforming existing models, emphasizing its effectiveness in improving recommendation accuracy by better handling contextual correlations and reducing the impact of less informative data points. Nawara and Kashef (2021) aimed to review and analyze Context-Aware Recommendation Systems (CARS) in IoT environments. The methodology involved a comprehensive review of existing literature on IoT-CARS, focusing on their requirements, characteristics, and applications. Findings highlighted the diverse ways IoT contexts are modeled in recommendation systems, and discussed metrics used to evaluate their performance, underscoring the importance of context in enhancing personalized recommendations in IoT settings.

Research gaps

The deficiency of scholarly literature about the ideal equilibrium between AI intervention and user control in e-commerce underscores the necessity of customized AI designs to augment customer contentment and involvement. Existing studies indicate that consumers are most affected when algorithms exert a moderate level of control, suggesting that excessive or insufficient AI intervention can negatively impact user experience. Further investigation is required into the demographic influences, such as age and income, on AI-driven consumer experiences. Specifically, how different age groups respond to AI recommendations and the role of income in purchasing decisions need more detailed analysis. There has been little research on how AI can improve users' ability to make decisions and increase the variety of items available to them, which has left the impact of AI components on giving consumers additional alternatives and choices understudied. Similarly, further research is needed to fully grasp how AI can effectively customize recommendations to individual tastes in the context of creating personalized customer experiences. Additionally, the potential of AI to innovate consumer strategies and update product recommendations needs more detailed examination, particularly in how AI can create innovative strategies that go beyond traditional recommendation systems. To close these gaps, this study will look at how AI intervention and user control interact, how demographics affect AI-driven experiences, how AI provides options and choices, how AI personalizes consumer experiences, and how AI is used to innovate consumer strategies.

Conceptual framework

The conceptual framework of this study looks into the most noteworthy and significant topics included in the research, as well as the role that e-commerce plays both before and after deep learning and machine learning is used to promote products. This paper composes six hypotheses to represent the practical measures and results of product recommendation systems.

Figure 1 depicts the conceptual framework of the research. AI-driven product recommendations are the central feature of the study, directly impacting productivity, sales, and consumer experience (H1a, H1b, and H1c). Consumer experience is further influenced by the age (H2) and income (H3) of the consumers. Product recommendations not only offer more options and choices (H4) but also help develop a personalized experience for consumers (H5). Additionally, AI contributes to updating new product launches and creating innovative strategies for consumers (H6).

The product recommendation improved productivity, sales and consumer experience

In E-commerce product recommendation is important because the sale of the products is dependent upon the recommendation. A product recommendation system helps the customers identify the product they are looking for and shows them the relevant product information at the appropriate time. An accurate recommendation improves the buying behavior of customers in e-commerce and makes them feel good about buying the products they are interested in. An appropriate product recommendation effectively improves the customer's experience in buying products, and the consumer's good experience improves productivity and sales. Consumers' good experiences improve the purchase of products in e-commerce and enhance the buying decision (Alrumiah & Hadwan, 2021).

H1a *AI-driven product recommendations can increase productivity.*

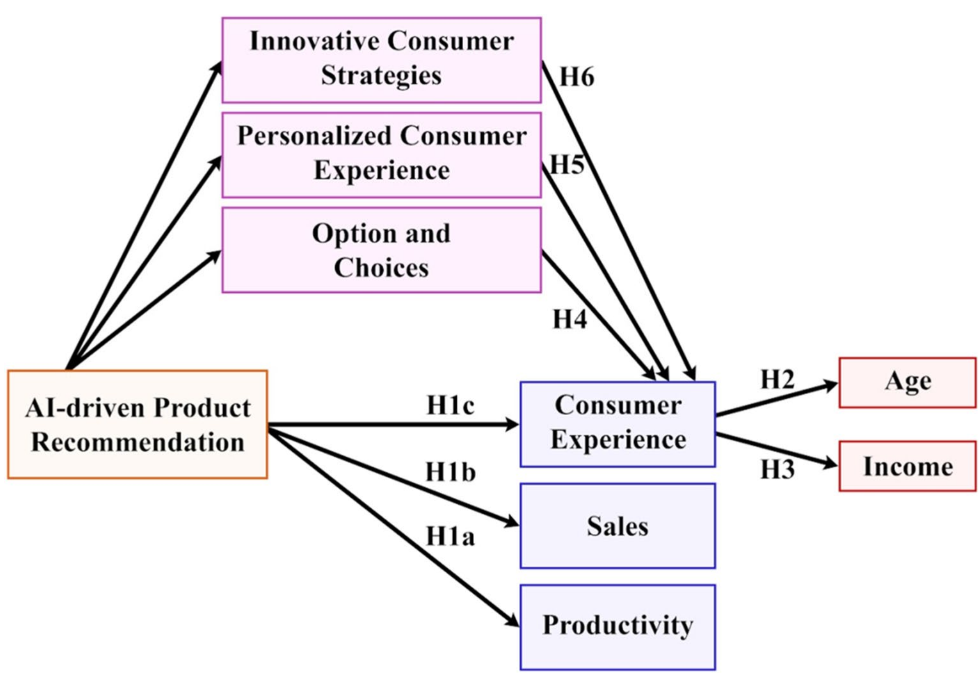
H1b *AI-driven product recommendation can enhance sales.*

H1c *AI-driven product recommendations can improve the consumer experience.*

Consumer experience depends upon the age of the consumer

Customer experience is the sum of the consumer's cognitive, emotional, and behavioral responses at all steps of the

Fig. 1 Conceptual framework



consumption process, including the stages before, during, and after a purchase (Bascur & Rusu, 2020). The "Age of the Customer" has taught us that consumers now have greater control over the purchasing process than they did in the past. In marketing research, the age of the customer is an important demographic factor. Customers of different age profiles will exhibit unique preferences, needs, and wants and it creates different behaviors. A teenager's bright and shiny buying choices will differ from those of an older person. In online shopping, most people are young because buying products online is very convenient for them as they can buy anytime anywhere (Lin et al., 2022). Older people have more emotional control and maturity than younger people, and this leads them to make different types of purchases. It shows that the customer's age influences their emotional control and maturity of the purchase. Therefore, the following hypothesis is proposed:

H2 *Consumer experience depends upon the age of the consumer*.

Income of the consumer is a factor for purchasing products

Income is the most important factor affecting the consumer's purchasing decision (Qazzafi, 2020). Income has the strongest ability to influence consumer purchasing behavior. When the customer has a higher level of income, their purchasing power is also higher. Customers with more disposable income can afford to buy more luxurious products. Consumers' income levels affect their purchasing patterns. Consumers in the lower to middle-income brackets typically allocate their income towards essential expenditures such as groceries and clothing. Many studies indicate that the level of consumer income influences their attitude toward the decision to purchase products (Chi et al., 2021). Thus, the following hypothesis was put out by the study:

H3 *The income of the consumer is a factor for purchasing products.*

Product recommendation provides more options and choices for the consumers

Product recommendations are one of the most powerful tools for recommending customer-wanted products in online shopping. Product recommendation is a vast area covering different aspects of user expectations, behavior, needs, interests, etc. (Deepak & Kasaraneni, 2019). When users search for a specific product on websites or apps, the product recommendation provides more options and choices to help customers locate the product they desire. Product recommendations provide consumers with a lot of options based on their expectations, behavior, needs, interests, and so on. For example, when buying a dress, based on consumer expectations, product recommendations provide a lot of choices regarding price, color, quality, supplier details, payment options, similar product details, etc. Customers' online purchasing decisions will be influenced if a recommendation banner is placed beneath the main product. Good product recommendation examples include similar items, products frequently bought together, items popular with other customers, and those recently viewed in the store. This type of recommendation provides a lot of choices to the customer when buying a product online. Therefore, the study proposed the following hypothesis:

H4 *Product recommendation provides more options and choices for the consumers*.

Product recommendation helps to develop a personalized experience for each consumer

"The tailoring of products and buying experience based on the individual consumer's personal and preference information" is known as personalization (Hallikainen et al., 2022). An online customization system adapts interaction and content to give users the most distinctive and pertinent online shopping interaction by concluding the user's profile, interests, and preferences. E-marketing and digital service innovations have made personalization likely in e-commerce. A recommendation agent is a remarkable new interactive decision aid; it helps consumers screen and evaluate various options that are available at e-commerce sites. Online recommendation systems are effective in engaging consumers, increasing consumer loyalty, cross-selling, and up-selling. Derived from the customer's product acquisition history, usage, and access history or cookie-based information, various types of personalization techniques are available. Personalized product recommendations (PRS) are when a website or app displays product recommendations according to the user's profile, behavior, taste, and preference. Personalized recommendation strategies leveraging deep learning techniques are pivotal in enhancing user engagement and satisfaction across digital platforms (Rane, 2023). These strategies harness advanced algorithms to analyze extensive user data, including browsing history, purchase patterns, and contextual cues like location and time (Sodiya et al., 2024). Deep learning excels in feature learning, enabling models to extract meaningful patterns and preferences automatically (Lakshmanan et al., 2020). Sequential recommendation models delve into temporal sequences of user interactions, adapting recommendations dynamically to evolving user preferences in areas such as fashion or media consumption (Deldjoo et al., 2020; Fang et al., 2020). An online customization system adapts interaction and content to give users the most distinctive and pertinent online shopping interaction concluding the user's profile, interests, and choices (Venkatachalam & Ray, 2022; Adomavicius et al., 2021). These approaches not only enhance the precision of personalization but also accommodate multimodal data integration, thereby offering richer insights into user preferences. Challenges like data privacy and computational complexity necessitate careful consideration, but these innovations represent a significant leap forward in optimizing user experience and driving business success in e-commerce and digital environments. Personalized product descriptions change how a product is presented to go better with other products the buyer has already purchased or viewed online. Effective personalized product recommendations offer customers a unique online shopping experience (Behera et al., 2020). Therefore, personalized recommendations help customers find the most appropriate products at the right time during their purchasing journeys, improving their online shopping experience. Therefore, the following hypothesis is proposed:

H5 *Product recommendation helps to develop a personalized experience for each consumer.*

AI not only helps product recommendation systems to update new launches but also creates innovative strategies for consumers

E-commerce merchants frequently present products and their specifications on a website before enabling users to make purchases (Zhang & Wang, 2021). Twenty years ago, techniques and concepts from other areas of AI were adapted to create recommender systems for personalized e-services, focusing on discovering user profiles and preferences. AI-driven applications have been a huge success in the past few years. The AI project achieved fame by winning against a professional human player in the game of 'Go'. Additionally, self-driving cars, computer vision, and speech recognition are major AI successes.

Companies can boost sales by using recommender systems on their websites, which use data and machine learning to suggest products that users might be interested in. Recommender systems are AI tools that help suggest items to users according to their preferences (Chinchanachokchai et al., 2021). AI, including computational intelligence and machine learning methods and algorithms, enhances the accuracy of predictions and cold start issues and solves the data scarcity of recommender systems. The product recommendation system's goal is to forecast customer interest and provide the recommended product based on customer interest. Recommender systems employ an array of AI techniques to enhance user experience and elevate consumer happiness.

ML techniques can create a predictive model that helps determine whether a new item is relevant to the user. ML algorithms in RS are classified into two categories: collaborative filtering based on user behavior and recommendation systems based on content. Content-based recommendation systems suggest things that match what a user has shown they like. The benefits of content-based recommendation systems include not suffering from data scarcity issues: recommending new items to users; capture the user's specific interests (Cami et al., 2019: Anand & Nath, 2020). In user-based collaborative filtering, products are evaluated and chosen in response to other users' reviews and comments. User-based collaborative filtering's main benefit is that it doesn't need knowledge of the particular content of the good or service (Thakkar et al., 2019; Chen et al., 2020).

AI success and advances nowadays have a significant impact in recommender systems to create innovative strategies for consumers. AI-driven product recommendation systems provide recommendations, offers, and price information regarding the consumer's searched products so that consumers can plan to buy them with their next paycheck or payment. A new era for recommender systems has been propelled by AI that produced detailed insights into the connections between users, products, and markets, discovered extensive knowledge in demographical, virtual, textural, and contextual data, and presented more complex data representations. Using AI in product recommendation can update newly launched products on the E-commerce site. Because AI-driven product suggestions provide individualized recommendations to customers and prospects with high expectations, they are essential in winning over consumers' hearts and minds. Thus, the present study proposes the following hypothesis:

H6 *AI not only helps product recommendation systems to update new launches but also creates innovative strategies for consumers.*

Three prominent theories provide a solid theoretical foundation for understanding the hypotheses in this study. According to the Theory of Planned conduct (TPB), attitudes, subjective norms, perceived behavioral control, and other factors, all affect behavioral intentions, which in turn influence actual conduct (Kashif et al., 2018). This theory provides a framework for understanding consumer actions regarding AI-driven product recommendations (Gupta et al., 2024; Mohr & Kühl, 2021; Sidlauskiene, 2022). For instance, H1b, which suggests that AI-driven product recommendations enhance sales, can be explained through TPB by examining how positive attitudes towards personalized recommendations and perceptions of control over purchasing decisions lead consumers to follow through with purchases. Similarly, H3, focusing on the impact of income on buying decisions, aligns with TPB's consideration of social norms and perceived control over behavior, where higher income may contribute to greater perceived control and willingness to engage with product recommendations. H4, highlighting that product recommendations offer more options, connects with TPB's emphasis on subjective norms, as recommendations can shape perceptions of what choices are socially endorsed or acceptable. Lastly, H5, which emphasizes the personalization of consumer experiences, aligns with TPB's focus on attitudes and perceived control, illustrating how tailored recommendations can enhance consumer satisfaction and loyalty by meeting individual preferences effectively. As a result, TPB offers a thorough theoretical framework for comprehending these theories in relation to AI-driven e-commerce settings.

Expectancy-Confirmation Theory posits that consumer satisfaction hinges on the alignment between pre-existing expectations and actual experiences with products or services (Tan et al., 2019; Rheu et al., 2024). According to this idea, the confirmation or disconfirmation of expectations can help explain H1c, which contends that AI-driven suggestions improve the user experience, in the context of AI-driven product recommendations. When AI algorithms accurately predict and recommend products that align with consumer preferences and needs, it reinforces positive expectations, leading to heightened satisfaction and perceived value (Gkikas & Theodoridis, 2022). Conversely, mismatches between recommendations and consumer expectations may result in dissatisfaction (Chen et al., 2022). Therefore, the Expectancy-Confirmation Theory offers a framework for comprehending how the quality and relevance of AI-driven recommendations directly impact consumer experiences by either confirming or challenging their initial expectations, thereby shaping overall satisfaction levels in e-commerce contexts.

According to the Technology Acceptance Model (TAM) (Zaineldeen et al., 2020; Mohd Amir et al., 2020), technology adoption and its subsequent impact on user behavior are greatly influenced by the perceived effectiveness and ease of use of the technology. About AI-powered product suggestions, TAM aligns with H1a, which suggests that these recommendations can enhance productivity. By emphasizing how AI tools streamline decision-making processes and improve operational efficiency, TAM underscores their perceived usefulness in enhancing productivity metrics within e-commerce environments (Khan et al., 2024). Moreover, TAM also relates to H6, highlighting that AI not only facilitates the timely updating of product recommendations but also fosters innovative strategies that cater to diverse consumer preferences. These theories collectively provide a theoretical foundation for comprehending the different ways that AI-driven product recommendations affect customer behavior, satisfaction, and overall business results in the e-commerce industry.

Methodology

Research design

To methodically assess the effects of AI-driven product recommendations on sales, productivity, and customer experience in the e-commerce industry, this study's research design uses a quantitative methodology. Purposive sampling was chosen to ensure that the sample consisted of individuals and businesses actively engaged in e-commerce, thereby providing relevant and insightful data. An online survey was used to gather data, and participants were chosen from a variety of Chinese regions that were recognized for having substantial e-commerce activity. This method facilitated the gathering of a diverse yet targeted sample, yielding responses from 439 consumers and 356 sellers. Lisrel 10.20 and Smart PLS 3 software were utilized to conduct a thorough analysis of the gathered data, guaranteeing a strong statistical assessment and verification of the suggested theories. To offer a thorough grasp of the variables impacting buyer and seller behaviors, this research approach is utilized to capture the subtle effects of AI on e-commerce.

Target population

This study's target population includes both buyers and sellers actively engaged in e-commerce within China. Consumers involved in the study represent a diverse demographic, spanning various age groups, income levels, and professions, who regularly engage in online shopping activities. The sellers, on the other hand, operate across different business types such as retail, wholesale, manufacturing, and services, varying in business size and income levels. This diverse group of participants from China provides a broad spectrum of insights into the dynamics of e-commerce, particularly in how AI-driven product recommendations impact consumer behavior, sales, and overall user engagement. The study aims to investigate how these elements interact within the context of deep learning-based recommendation systems, aiming to enhance both user satisfaction and business performance in the digital marketplace.

The present study's target demographic, consisting of Chinese customers and vendors, was selected based on multiple persuasive factors. First off, China is one of the largest and fastest-expanding e-commerce markets globally, which makes it a perfect place to research how AI-driven product recommendations affect buyer behavior and seller tactics. The consumer group's demographic diversity guarantees a thorough investigation of how different segments perceive and respond to AI-enhanced shopping experiences. Similarly, the sellers involved span multiple business types and sizes, reflecting the breadth of the e-commerce ecosystem and allowing for insights into how different business models adapt to and utilize AI technologies.

Furthermore, the rationale for selecting this population lies in China's technological advancement and widespread adoption of AI in e-commerce practices. By concentrating on this area, the analysis can gather detailed information about how well deep learning-based recommendation systems work to improve user engagement, sales, and the general customer experience. The data collected from this diverse group aims to contribute valuable empirical evidence to inform strategies aimed at optimizing AI applications in e-commerce, thereby benefiting both consumers and businesses operating within this dynamic marketplace.

Sampling strategy and sample collection

Purposive sampling was employed in this study to selectively recruit participants based on specific criteria deemed crucial for looking at how AI is affecting the dynamics of Chinese e-commerce. Purposive sampling was chosen to facilitate a deeper exploration of the role of AI in e-commerce by focusing on participants with direct involvement and expertise in relevant industry practices. This approach ensured that the study's findings were grounded in real-world applications and could provide actionable insights for stakeholders in the e-commerce sector in China. The criteria included involvement in e-commerce as either sellers or buyers, ensuring that participants had direct experience and knowledge relevant to the study's objectives. This focused strategy sought to obtain in-depth information from people who could offer insightful viewpoints on AI technologies in the context of online retail. For sellers, participants were identified from various sectors within the e-commerce industry, such as retail, wholesale, manufacturing, services, and specialized e-commerce platforms. Selection criteria prioritized individuals or businesses actively utilizing AI-based tools like product recommendation systems or predictive analytics to enhance sales and consumer engagement. Buyers were selected based on their frequent engagement in online shopping activities across diverse product categories. This included consumers who regularly make purchases through e-commerce platforms, providing insights into how AI influences their purchasing decisions and overall shopping experiences.

The study began by identifying potential participants through various channels known for their active involvement in e-commerce activities in China. These channels include e-commerce platforms, industry associations, professional networks, and online communities focused on AI and technology in commerce. Using purposive sampling, the research team reached out to individuals and businesses known or suspected to utilize AI technologies in their e-commerce operations. This involved contacting e-commerce businesses, both large and small, across different sectors such as retail, wholesale, manufacturing, and specialized e-commerce platforms.

A set of specified criteria related to the study's goals was used to screen participants. Businesses utilizing AI-driven technologies, such as automated customer support, predictive analytics, or product suggestion systems, were among the requirements for Sellers. For buyers, the criteria included individuals who frequently engage in online shopping across various product categories and platforms utilizing AI-enhanced features. A concise explanation of the study's objectives was given to potential participants, along with an emphasis on the value of their views regarding how AI affects e-commerce performance. This approach aimed to foster interest and secure participation by highlighting the study's potential contribution to understanding and improving e-commerce practices.

An online survey was used to gather data, and participants were chosen from a variety of Chinese regions recognized for having substantial e-commerce activity. The questionnaire was designed to capture detailed information on participants' demographics, strategies for adopting AI, opinions on recommendations made by AI, and how these affect output and customer satisfaction. Upon collection, responses were screened to exclude incomplete or irrelevant data, maintaining the quality and reliability of the dataset. Finally, the study's sample consists of 356 merchants and 439 consumers. The software programs Lisrel 10.20 and Smart PLS 3 were used to analyze the gathered data. The effect of AI on e-commerce performance was hypothesized, and correlations between variables were examined and tested using statistical analytic techniques including SEM.

Participant details

Figure 2 shows the demographic details of the 439 consumers that participated in this study's survey. With 225 female participants (51.25%) and 214 male participants (48.75%), the gender distribution is about even. The age group of 25–34, accounts for the large number of participants (129,

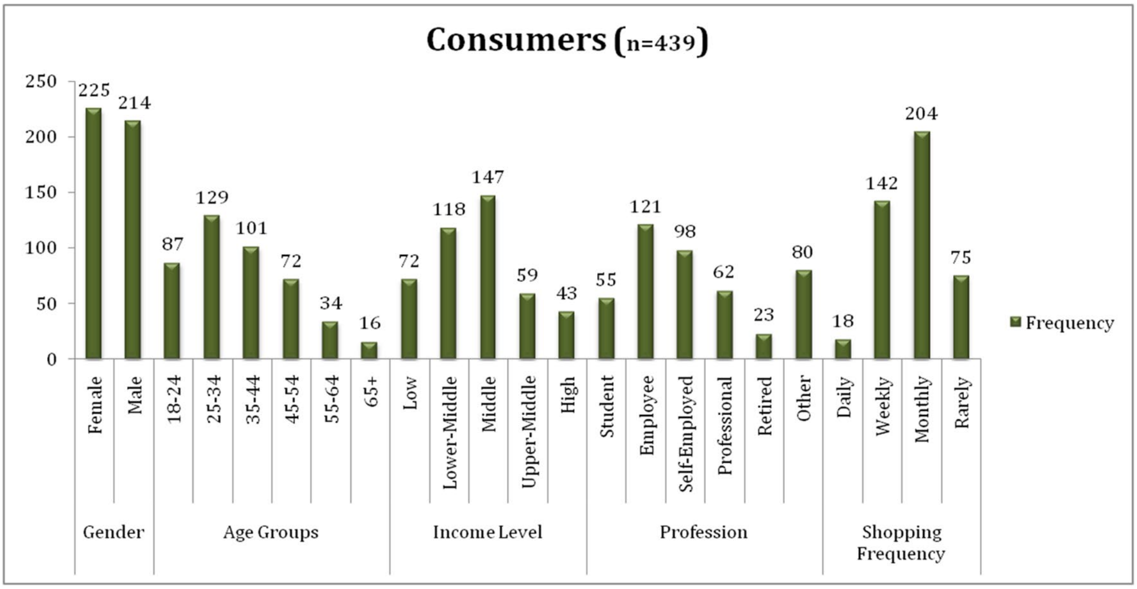


Fig. 2 Demographic details of the consumers

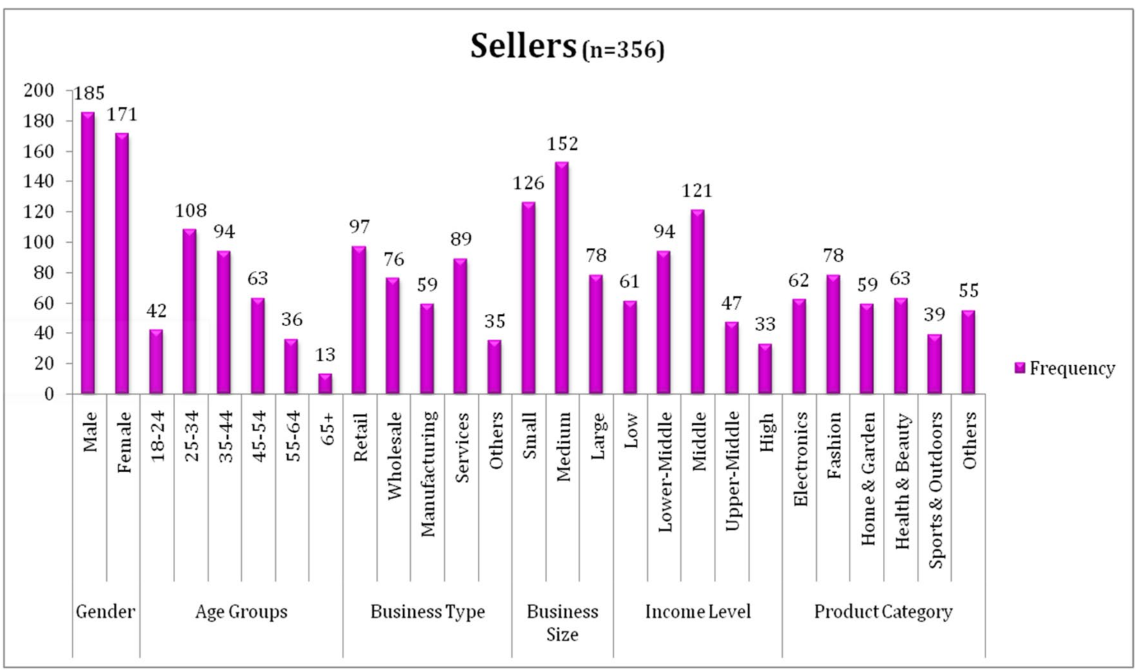


Fig. 3 Demographic details of the sellers (356)

29.39%), followed by 35–44 (101, 22.99%), with fewer participants in the later age groups (55 and above). In terms of income levels, most participants are in the middle-income category (147 participants, 33.49%), followed by the lower-middle-income category (118 participants, 26.88%), with fewer participants in the high-income category (43 participants, 9.80%).

The largest professional group is employees (121 participants, 27.56%), followed by self-employed individuals (98 participants, 22.32%), with students, professionals, retired individuals, and those in other categories making up the rest of the sample. Shopping frequency data indicates that most participants make purchases on a monthly basis (204 participants, 46.47%), followed by those who shop weekly (142 participants, 32.35%), with a smaller percentage shopping daily (18 participants, 4.10%) or rarely (75 participants, 17.08%). Overall, this study captured a diverse group of consumers, aiming to provide a rich dataset for analysis.

Figure 3 presents the details of the 356 sellers in this study. The gender distribution among sellers shows a slight majority of males (185 sellers, 52.25%) compared to females (171 sellers, 47.75%). Age-wise, the largest group falls within the 25–34 age bracket (108 sellers, 30.34%), followed by those aged 35–44 (94 sellers, 26.40%), with fewer sellers in older age groups. In terms of business types, the majority are involved in retail (97 sellers, 27.25%), followed closely by services (89 sellers, 25.00%) and wholesale (76 sellers, 21.35%), with a smaller representation in manufacturing and other types of businesses. Business sizes vary, with medium-sized enterprises comprising the largest group (152 sellers, 42.70%), followed by small-sized enterprises (126 sellers, 35.40%) and larger enterprises (78 sellers, 21.91%). Income levels among sellers predominantly cluster around the middle-income category (121 sellers, 34.04%), with lower-middle and upper-middle income categories also represented, and fewer sellers in the high-income bracket. Product categories span electronics (62 sellers, 17.42%), fashion (78 sellers, 21.91%), home & garden (59 sellers, 16.57%), health & beauty (63 sellers, 17.70%), sports & outdoors (39 sellers, 10.96%), and other categories (55 sellers, 15.45%). This demographic profile provides an understanding of the sellers involved in the study, highlighting their diversity across various demographic and business dimensions.

Measurement scaling

The present investigation employed a 5-point Likert scale as a commonly used instrument to assess attitudes, views, and perceptions. Participants rated how much they agreed with statements on customer experiences, buying habits, and AI-driven product recommendations. The respondents were able to indicate different levels of agreement or disagreement using a scale that went from 1 (Strongly Disagree) to 5 (Strongly Agree). This approach provided nuanced insights into how AI impacts user engagement, sales, and personalized experiences in e-commerce settings. Data collected through the Likert scale were analyzed to uncover trends, correlations, and statistical significance, aiding in the study's conclusions and recommendations for optimizing AI strategies in online commerce environments.

Ethical considerations

Informed consent Before beginning the study, every participant was made aware of its goals, methods, possible dangers, and advantages. Prior to filling out the questionnaire, participants electronically gave their informed consent. They received guarantees that their involvement in the study was completely voluntary and that participants would not face any repercussions if they chose to leave at any point.

Confidentiality and anonymity Participants' privacy and identity were rigorously protected. All data were safely saved in encrypted files that were only accessible by the research team, and personal identities were eliminated from the dataset. To keep participant responses anonymous, each participant was given a unique code.

Participant well-being The study design ensured minimal risk to participants. The questionnaire was reviewed to ensure that it did not involve any sensitive or potentially unsettling questions. Participants were given contact details for support services in case they experienced any discomfort during or after the survey.

Data handling and security Data collection, storage, and analysis procedures complied with relevant data protection regulations. Data were collected through a secure online platform, and all electronic data were stored on password-protected servers. Physical copies of data were kept in a locked cabinet.

Transparent reporting Participants were made aware of how their data would be utilized, including publication and potential sharing with other researchers. They were assured that their data would only be used for the purposes outlined in the consent form and that findings would be reported in aggregate form, ensuring individual anonymity. Incorporating ethical considerations into the analysis throughout the data analysis process, ethical considerations were upheld. Only anonymized data were used, and analyses were conducted in a way that respects participant confidentiality. Results were presented in aggregate form, avoiding any potential identification of individual participants.

Estimation techniques

SEM was the estimating method used in this investigation to examine the data gathered and evaluate the suggested hypotheses. SEM was selected to analyze the complex effects of AI-driven product recommendations on e-commerce success because of its ability to handle intricate interactions between observable and latent variables. First, CFA was used inside the SEM framework to evaluate the validity and reliability of the data. This step ensured that the measurement models for each construct were valid and reliable. The CFA provided factor loadings, which helped confirm that the items used to measure each construct were appropriate and contributed meaningfully to the underlying concept. For hypothesis testing, path analysis was conducted using SEM to ascertain how AI-driven product recommendations affect the study variables both directly and indirectly. This approach allowed the study to simultaneously evaluate multiple relationships and provided a thorough comprehension of the ways in which AI affects several facets of consumer behavior and corporate consequences. The overall model fit was assessed using goodness-of-fit indices, such as the Root Mean Square Error of Approximation (RMSEA), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI). These indices helped ensure that the proposed structural model accurately represented the data and provided a good fit. The estimation techniques employed in this study were guided by the methodologies outlined in Ahmed et al. (2024). Thus, SEM was utilized in this study to rigorously analyze the data and test the proposed hypotheses, offering a detailed and reliable examination of the impacts of AI in e-commerce. This approach enabled the study to capture the complexity of the relationships among the variables and provided insights into how AI-driven recommendations can enhance productivity, sales, and consumer experiences.

Results

This section provides a thorough assessment of the fit of the suggested model, taking into account the structural model, measurement model, goodness of fit, and findings from the recurrent neural network (RNN) study. The evaluation covers various fit indices, validity, and reliability measures, confirming the robustness of the SEM and validating the research hypotheses. The analysis reveals significant positive relationships between AI-driven product recommendations and productivity, sales, and consumer experience, with additional insights from RNN predictions, reinforcing the study's findings.

Table 1 Evaluation of overall model fit indices and criteria

Fit Index	Value	Good Fit Criterion
$\chi 2$/df (chi-square normalized by degrees of freedom)	3.2	Less than 5
RMSEA (Root Mean Square Error of Approximation)	0.07	$\leq$0.08 is a good fit
NFI (Normed Fit Index)	0.92	$\geq$0.9 is a good fit
NNFI (Non-Normed Fit Index)	0.91	$\geq$0.9 is a good fit
CFI (Comparative Fit Index)	0.93	$\geq$0.9 is a good fit
IFI (Incremental Fit Index)	0.94	$\geq$0.9 is a good fit
RFI (Relative Fit Index)	0.92	$\geq$0.9 is a good fit
RMR (Root Mean Square Residual)	0.04	$\leq$0.05 is a good fit
Standardized RMR	0.03	$\leq$0.05 is a good fit
GFI (Goodness of Fit Index)	0.91	$\geq$0.9 is a good fit
Overall Model Fit (LISREL Estimates)	Met a goodness of fit standard	Research models expected to be robust

Evaluation of the goodness of fit

This section assesses to determine the degree to which the data conforms to the model. It focuses on confirming the measurement model's validity and reliability and examining the importance of the structural model's coefficients.

Overall model fit

The suitability of the SEM employed in the investigation is assessed by the overall model fit evaluation in Table 1. The model's chi-square statistic, normalized by degrees of freedom, is within reasonable bounds for a satisfactory fit, according to the χ^2/df value of 3.2. A close fit between the model and the data is shown by an RMSEA of 0.07, which is less than the 0.08 requirement. A significant alignment between the model and observed data is indicated by key indices like NFI (0.92), NNFI (0.91), CFI (0.93), IFI (0.94), RFI (0.92), and GFI (0.91), all of which above the 0.9 criterion. The RMR (0.04) and Standardized RMR (0.03) are both below 0.05, indicating minimal residual error and further supporting the model's fit. Overall, LISREL estimates affirm that the model meets established standards for goodness of fit, underscoring its robustness in accurately capturing relationships among variables as hypothesized in the research.

Measurement model fit

The Model of Measurement Fit evaluates latent variables' dependability and validity and their indicators in relation to predetermined thresholds, ensuring the robustness of the measurement within the research framework (Hair et al., 2012; Goretzko et al., 2024). Each variable in Table 2 undergoes assessment based on three key criteria. CFA measures the degree of correlation between each indicator and its hidden variable; to assure accurate assessment, values above 0.70 are usually the goal (Jian et al., 2020; Carvalho & Sarkar, 2018). Composite Reliability (CR) measures the internal consistency of the latent variable, with values above 0.70 indicating reliable measurement across indicators (Baharum et al., 2023; Ismail et al., 2020). Variance Extracted (VE) quantifies how much variability in the indicators is explained by the latent variable, with values above 0.50 suggesting sufficient explanation of variability (Libório et al., 2020). Together, these standards verify the validity and reliability of the measurement model and guarantee that every variable accurately reflects the intended construct in the context of the study. In this analysis, all variables exceed these thresholds, indicating a strong measurement model fit. For example, APR has a CFA ranging from 0.75 to 0.88, CR of 0.82, and VE of 0.79, indicating that it reliably measures the underlying construct. Similar patterns are observed across each variable, demonstrating robust measurement qualities. Overall, adherence to these thresholds ensures that the measurement model effectively captures and validates the connections between variables in the structural model, supporting the study's theoretical framework and research hypotheses.

Table 2 Measurement model fit of latent variables

Variable	Indicator	CFA	CR	VE	Notes
AI-driven Product Recommendation (APR)			0.823456	0.789012	Reliable
	APR1	0.86			Valid
	APR2	0.75			Valid
	APR3	0.79			Valid
	APR4	0.88			Valid
Productivity (P)			0.834567	0.654321	Reliable
	P1	0.92			Valid
	P2	0.75			Valid
	P3	0.83			Valid
	P4	0.78			Valid
Sales (S)			0.876543	0.623456	Reliable
	S1	0.91			Valid
	S2	0.87			Valid
	S3	0.76			Valid
Consumer Experience (CE)			0.789012	0.712345	Reliable
	CE1	0.94			Valid
	CE2	0.89			Valid
	CE3	0.81			Valid
Age (A)			0.845678	0.565432	Reliable
	A1	0.73			Valid
	A2	0.96			Valid
	A3	0.85			Valid
Income (I)			0.812345	0.598765	Reliable
	I1	0.72			Valid
	I2	0.77			Valid
	I3	0.93			Valid
Options and Choice (OC)			0.876543	0.732189	Reliable
	OC1	0.80			Valid
	OC2	0.74			Valid
Personalized Consumer Experience (PCE)			0.843279	0.716742	Reliable
	PCE1	0.85			Valid
	PCE2	0.92			Valid
	PCE3	0.78			Valid
Innovative Consumer Strategies (ICS)			0.739528	0.659834	Reliable
	ICS1	0.81			Valid
	ICS2	0.76			Valid
	ICS3	0.89			Valid

The rotated component matrix reveals distinct relationships among the variables (Table 3). Component 1 is characterized by APR, A, and I, indicating demographic influence on AI recommendations. Component 2 features P and I, suggesting income-related productivity. Component 3 involves S, OC, and PCE, reflecting sales and consumer decision-making. Component 4 shows CE, PCE, and ICS, emphasizing consumer experience and innovative strategies. These components illustrate interactions within AI recommendations and e-commerce, offering insights into consumer behavior and business outcomes.

Table 4 presents an assessment of intrinsic coherence convergent validity and dependability for each variable in the study. Cronbach's Alpha and rho_A are used to assess internal consistency reliability; values above 0.70 indicate that each variable's items consistently measure the same underlying construct (Rheeders & Meyer, 2022). Average Variance Extracted is used to evaluate convergent validity (AVE). When the AVE value is more than 0.50, the variables adequately explain the variance in their indicators, demonstrating good convergent validity (Ismail et al., 2020). Together, these measures guarantee the measurement model's applicability and robustness for precise interpretation and additional research in the study.

How highly each item correlates with its corresponding latent variable concerning other latent variables is revealed by the cross-loading results in Table 5. For each item, the highest loading should be on the latent variable it is intended to measure, demonstrating discriminant validity. For instance, Compared to other latent variables like P, S, CE, A, I, OC, PCE, and ICS, APR1 has a larger loading on the APR latent variable (0.76). Every item in this pattern has a stronger correlation with its corresponding latent variable than with any other latent variable, suggesting that this pattern is constant across all items. This suggests that the items are effectively measuring their intended constructs, supporting the overall measurement model's validity.

Table 6 presents the findings from the Heterotrait-Monotrait and the Fornell & Larcker discriminant validity analysis. By comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations between the constructs, the Fornell & Larcker criterion evaluates discriminant validity (Ab Hamid et al., 2017). The square root of the AVE (diagonal values) must be greater than the correlations (off-diagonal values) between

Table 3 Rotated component matrix

Variable	Component 1	Component 2	Component 3	Component 4
APR	0.86	-0.12	0.25	0.08
P	0.05	0.92	-0.15	0.04
S	0.12	0.07	0.88	-0.10
CE	0.18	0.20	0.07	0.89
A	0.89	-0.05	-0.12	0.15
I	0.26	0.85	0.22	-0.18
OC	0.23	0.09	0.30	0.75
PCE	0.17	0.18	0.35	0.81
ICS	0.20	0.25	0.28	0.79

Table 4 Internal consistency reliability and convergent validity

Variable	Internal Consistency Reliability		Convergent validity
	Cronbach's Alpha	rho_A	Average Variance Extracted (AVE)
APR	0.889	0.879	0.651
P	0.875	0.912	0.702
S	0.849	0.843	0.664
CE	0.892	0.825	0.778
A	0.862	0.901	0.691
I	0.896	0.835	0.623
OC	0.834	0.867	0.606
PCE	0.834	0.877	0.643
ICS	0.859	0.838	0.683

the constructs for discriminant validity to be proven. The square root of the AVE for each construct in this study (values on the diagonal) is larger than the correlations between constructs (off-diagonal values), according to the Fornell & Larcker criterion. As an illustration, the AVE's square root for APR is 0.81, greater than its connection with P (0.52), S (0.48), and so forth. Given that each construct has more variance with its indicators than with other constructs, this suggests excellent discriminant validity.

Another technique for evaluating discriminant validity is the HTMT ratio, which compares the ratio of within-trait correlations to between-trait correlations (Belay et al., 2021). Less than 0.85 is a generally recognized cut-off point for HTMT (Ab Hamid et al., 2017). All of the HTMT values in this investigation are below the 0.85 threshold, according to the HTMT ratios, demonstrating strong discriminant validity. For example, the HTMT ratio of 0.61 between APR and P is far below the cutoff. This implies that there is little to no overlap between the constructs and that they are separate. Overall, the HTMT ratios and the Fornell & Larcker criterion both validate the discriminant validity of the study's notions, showing that they are sufficiently different from one another.

Hypothesis analysis

The findings from Table 7 underscore the robust support for all hypotheses examined in this study.H1 shows that AI-driven Product Recommendations (APR) and Productivity (P), Sales (S), and Consumer Experience (CE) have a substantial positive association ($\beta = 0.68$, $p < 0.001$) that accounts for 46% of their variation (R-squared = 0.46, F-squared = 0.25). Secondly, H2 and H3 both demonstrate that Consumer Experience (CE) is strongly influenced by both Age (A) ($\beta = 0.52$, $p < 0.001$) and Income (I) ($\beta = 0.55$, $p < 0.001$), explaining 27% (R-squared = 0.27, F-squared = 0.20) and 30% (R-squared = 0.30, F-squared = 0.22) of their variances, respectively.

H4 through H6 confirm sequential paths where APR to Options and Choices (OC) to CE ($\beta = 0.60$, $p < 0.001$), APR to Personalized Consumer Experience (PCE) to CE ($\beta = 0.58$, $p < 0.001$), and APR to Innovative Consumer Strategies (ICS) to CE ($\beta = 0.63$, $p < 0.001$) all significantly influence CE, explaining 36% (R-squared = 0.36, F-squared = 0.24), 34% (R-squared = 0.34, F-squared = 0.23), and 39% (R-squared = 0.39, F-squared = 0.26) of its variance, respectively. These results collectively demonstrate strong statistical significance ($p < 0.001$) and highlight the substantial impact of APR on enhancing various aspects of consumer behavior and experience in e-commerce settings.

The SEM path analysis (Fig. 4) illustrates the relationships between latent variables, showing that APR significantly enhances P, S, and CE. CE positively correlates with A and I. Effective product recommendations increase OC and enhance CE, while PCE positively impacts CE. ICS is also significantly influenced by APR, boosting CE.

Recurrent neural networks (RNNs)

Artificial neural networks (ANNs) of the sort called RNNs are made to identify patterns in data sequences, including time-series data or natural language (Hewamalage et al., 2021). RNNs have connections that create directed cycles, in contrast to conventional feedforward neural networks, which enable information to remain across steps in the sequence (Chen & Li, 2021). Because of this property, RNNs are especially well-suited for jobs where the sequence in which the data points are processed is important, including trend prediction over time or processing sequential data for product suggestions in e-commerce. In this study, RNNs were utilized to examine the effects of consumer age and income on productivity, sales, and the consumer experience as well as the effects of AI-driven product recommendations. A summary of the RNN training and validation outcomes is provided in Table 8. The training accuracy improved consistently across epochs, starting at 55% and

Table 5 Cross loading

Items	APR	*P*	S	CE	A	I	OC	PCE	ICS
APR1	0.76	0.45	0.43	0.41	0.38	0.42	0.44	0.47	0.46
APR2	0.72	0.48	0.44	0.40	0.37	0.41	0.43	0.46	0.45
APR3	0.74	0.47	0.45	0.42	0.36	0.39	0.41	0.44	0.42
APR4	0.78	0.46	0.43	0.44	0.39	0.40	0.42	0.45	0.47
P1	0.44	0.79	0.47	0.45	0.40	0.38	0.41	0.43	0.42
P2	0.42	0.77	0.46	0.42	0.39	0.37	0.43	0.42	0.40
P3	0.43	0.75	0.44	0.43	0.38	0.36	0.40	0.41	0.41
P4	0.45	0.76	0.45	0.41	0.37	0.35	0.42	0.40	0.39
S1	0.41	0.45	0.78	0.43	0.39	0.41	0.42	0.44	0.40
S2	0.40	0.44	0.79	0.42	0.38	0.40	0.41	0.43	0.41
S3	0.42	0.43	0.76	0.41	0.37	0.39	0.40	0.42	0.39
CE1	0.44	0.45	0.43	0.81	0.40	0.41	0.42	0.45	0.44
CE2	0.42	0.43	0.41	0.80	0.39	0.40	0.41	0.44	0.42
CE3	0.43	0.41	0.40	0.79	0.38	0.38	0.40	0.43	0.41
A1	0.39	0.40	0.38	0.37	0.75	0.41	0.40	0.42	0.41
A2	0.37	0.38	0.37	0.36	0.76	0.40	0.39	0.41	0.40
A3	0.36	0.37	0.35	0.34	0.74	0.38	0.37	0.40	0.39
I1	0.42	0.39	0.38	0.37	0.40	0.76	0.41	0.42	0.38
I2	0.41	0.38	0.37	0.36	0.39	0.75	0.40	0.41	0.41
I3	0.44	0.37	0.36	0.35	0.38	0.74	0.39	0.40	0.40
OC1	0.43	0.36	0.39	0.38	0.40	0.41	0.79	0.43	0.41
OC2	0.42	0.39	0.38	0.37	0.39	0.40	0.78	0.42	0.40
PCE1	0.45	0.41	0.41	0.39	0.41	0.42	0.43	0.80	0.38
PCE2	0.44	0.40	0.40	0.38	0.40	0.41	0.42	0.79	0.34
PCE3	0.43	0.39	0.39	0.37	0.39	0.40	0.41	0.78	0.41
ICS1	0.47	0.42	0.42	0.40	0.4	0.43	0.44	0.46	0.78
ICS2	0.40	0.41	0.40	0.39	0.41	0.42	0.43	0.45	0.77
ICS3	0.48	0.40	0.39	0.38	0.40	0.41	0.42	0.44	0.79

reaching 82% by the fifth epoch. Similarly, the validation accuracy increased from 50 to 75%, showing that the model was successfully applying what it had learned from the training set to new data. The validation loss dropped from 1.30 to 0.85 and the training loss from 1.20 to 0.60, respectively, showing that the model was effectively minimizing the error throughout training. The model appears to be functioning well on both the training and validation datasets and was not overfitting based on the convergence of the training and validation losses. These results support the proposed hypothesis that AI-driven product recommendations can enhance productivity, sales, and consumer experience, as the model shows high accuracy and low loss values in predicting these outcomes based on the provided data. The RNN model used in this study consisted of a series of layers made to record the data's sequential dependencies. One LSTM (Long Short-Term Memory) layer with 100 units to learn long-term dependencies, an input layer to process the sequence data, and a dropout layer with a rate of 0.2 to prevent overfitting were all included in the architecture. a dense layer that outputs the final prediction using a sigmoid activation function. This architecture was chosen to effectively capture the patterns in the e-commerce data and to provide robust predictions on the impact of AI-driven product recommendations.

Discussion

The study's conclusions, which highlight the revolutionary effect of AI on customer engagement, are consistent with earlier research findings. Misra et al. (2024) emphasized the importance of customized AI designs in raising customer satisfaction and control, which supports the current findings those AI-driven product recommendations can improve consumer experience (H1c). The study by Asante et al. (2023) demonstrated that AI elements such as chatbots and recommendation systems boost consumer engagement, resonating with the present results indicating that AI-driven product recommendations enhance sales (H1b) and provide a personalized experience (H5). Furthermore, Sheshadri et al. (2024) underscored the function of AI in personalized marketing, which is in line with the results of the current study, which show that by customizing marketing messages to each unique customer's preferences, AI-driven recommendations boost

Table 6 Comparison of discriminant validity by Fornell & Larcker and the heterotrait-monotrait

	FORNEL & LARCKER									HETEROTRAIT MONOTRAIT								
	APR	P	S	CE	A	I	OC	PCE	ICS	APR	P	S	CE	A	I	OC	PCE	ICS
APR	0.81																	
P	0.52	0.80								0.61								
S	0.48	0.57	0.82							0.58	0.63							
CE	0.46	0.54	0.50	0.84						0.57	0.61	0.59						
A	0.43	0.50	0.46	0.45	0.79					0.52	0.56	0.54	0.53					
I	0.45	0.48	0.47	0.44	0.48	0.78				0.55	0.59	0.57	0.56	0.55				
OC	0.44	0.49	0.45	0.42	0.46	0.47	0.81			0.54	0.58	0.55	0.54	0.53	0.57			
PCE	0.47	0.52	0.48	0.45	0.43	0.46	0.50	0.83		0.56	0.60	0.58	0.57	0.55	0.59	0.61		
ICS	0.46	0.51	0.47	0.45	0.42	0.45	0.48	0.49	0.80	0.55	0.59	0.56	0.55	0.54	0.58	0.60	0.62	

productivity (H1a). Dudzinskaite et al. (2024) found that personalized content and clear messaging significantly enhance engagement, mirroring this exploration's results that AI recommendations improve consumer experience (H1c) and offer more options and choices (H4). Tula et al. (2024) emphasized the importance of strategic AI integration and ethical considerations, reinforcing the need for responsible AI practices to drive sustainable growth and innovation (H6).

The technological advancements in recommender systems, as discussed by Ko et al. (2022), highlight the potential of these systems to drive business growth and innovation. The present study's findings that AI-driven product recommendations enhance sales (H1b) and provide personalized experiences (H5) align with the observed business applications of recommendation systems across various industries. Javed et al. (2021) explored context-aware and context-based recommendation systems, which support the hypothesis that AI recommendations can increase productivity (H1a) by filtering and analyzing user interactions effectively. Jesse and Jannach (2021) examined the integration of digital nudging mechanisms into recommendation systems to guide user choices, which relates to the current investigation's finding that AI-driven recommendations improve consumer experience (H1c) by offering tailored suggestions. Tran et al. (2021) emphasized the accuracy and effectiveness of healthcare recommender systems, aligning with this examination's results that AI recommendations enhance sales (H1b) and provide more options and choices for consumers (H4). Ferrari et al. (2021) challenged the assumption of deep learning's superiority in recommender systems, suggesting that simpler approaches might be more effective, which is a consideration for future research on optimizing AI recommendation methodologies (H6).

This study's findings that AI-driven product recommendations enhance sales (H1b) and improve consumer experience (H1c) are supported by Chen et al. (2022), who found that AI capabilities significantly enhance firm performance through creative and AI-driven decision-making processes. Fonseka et al. (2022) noted that AI utilization enhances business performance, resonating with this analysis results that AI-driven recommendations increase productivity (H1a) and sales (H1b). Bawack et al. (2022) emphasized the importance of recommender systems and personalization in e-commerce, which aligns with the findings on the positive impact of AI on consumer experience (H1c) and personalized experiences (H5). Areiqat et al. (2021) highlighted AI's role in revolutionizing e-commerce through personalized services and predictive analytics, supporting the hypothesis that AI recommendations offer more options and choices (H4) and create innovative consumer strategies (H6). Lastly, von Zahn et al. (2022) addressed AI fairness in

Table 7 Hypothesis analysis

Hypothesis	Path	β	S.E	*p*-value	t-value	*R*-squared	F-squared	Acceptance status
H1	APR→P + S + CE	0.68***	0.05	< 0.001	13.60	0.46	0.25	Accepted
H2	CE→A	0.52***	0.04	< 0.001	13.00	0.27	0.20	Accepted
H3	CE→I	0.55***	0.04	< 0.001	13.75	0.30	0.22	Accepted
H4	APR→OC→CE	0.60***	0.05	< 0.001	12.00	0.36	0.24	Accepted
H5	APR→PCE→CE	0.58***	0.04	< 0.001	14.50	0.34	0.23	Accepted
H6	APR→ICS→CE	0.63***	0.05	< 0.001	12.60	0.39	0.26	Accepted

****p < 0.001*

Fig. 4 SEM path analysis

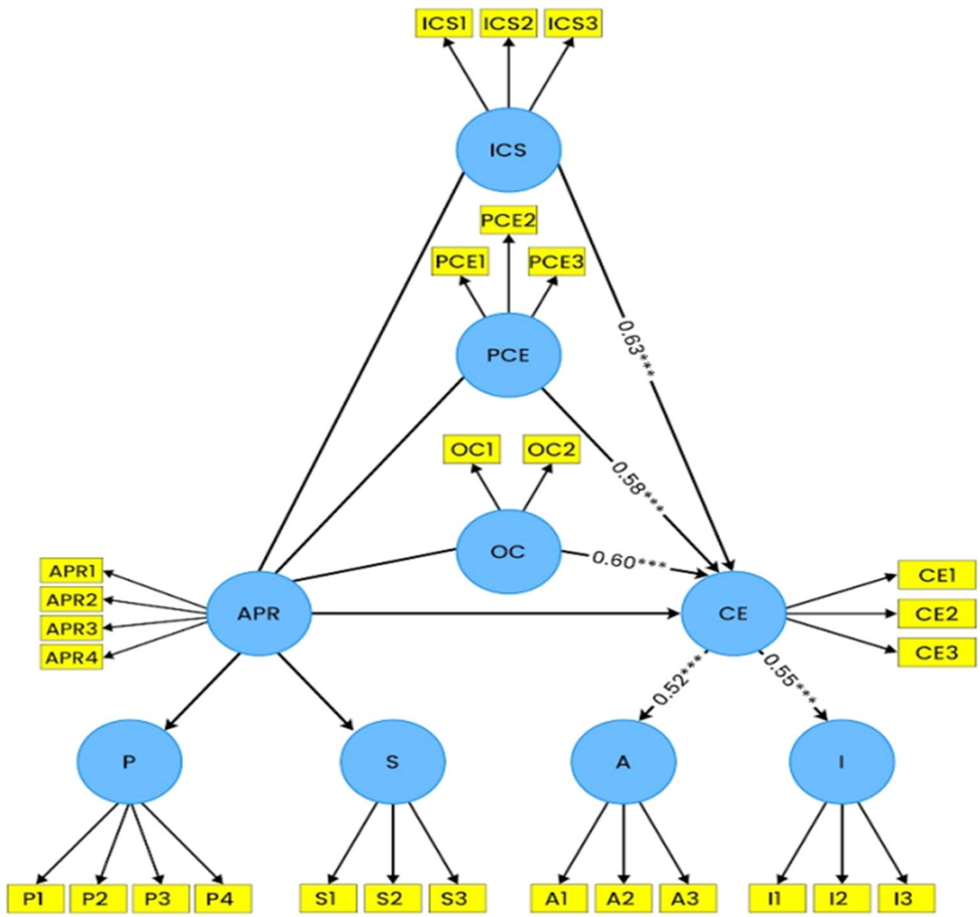


Table 8 RNN training and validation results

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.55	0.50	1.20	1.30
2	0.65	0.60	0.90	1.10
3	0.72	0.65	0.80	1.00
4	0.78	0.70	0.70	0.90
5	0.82	0.75	0.60	0.85

e-commerce, suggesting the need for equitable outcomes, which is a critical consideration for ensuring that AI-driven recommendations cater to diverse consumer demographics and preferences (H2, H3). By offering empirical data on the effects of AI-driven product suggestions on numerous facets of consumer behavior and business performance, this study adds to the body of knowledge already in existence. The findings support the theoretical frameworks proposed by previous studies, confirming the benefits of AI for sales, personalization, and customer engagement. Furthermore, by providing fresh perspectives on the moderating impacts of customer demographics like age (H2) and income (H3) on purchase behavior, this study emphasizes the significance of context-aware and tailored AI tactics.

The aim of this study is to gain a deeper comprehension of how AI-driven product recommendations affect user engagement and sales in the e-commerce industry, while the primary focus has been on improving product recommendations through deep learning and machine learning techniques, an equally important aspect is the optimization of dynamic pricing strategies. Dynamic pricing is a tactic that enables e-commerce sites to instantly modify prices in response to several variables is crucial for maximizing revenue and improving the overall consumer experience. Dynamic pricing utilizes algorithms to analyze market demand, competitor prices, consumer behavior, and other relevant data to set optimal prices. Making these algorithms more accurate and efficient depends heavily on AI and machine learning. By integrating deep learning models, e-commerce platforms can better predict consumer purchasing patterns, allowing for more responsive and flexible pricing strategies. The study's hypotheses implicitly touch upon elements that can be extended to dynamic pricing optimization. AI-driven product recommendations can boost productivity and sales by presenting consumers using appropriate products at appropriate times. When coupled with dynamic pricing, this can lead to optimized sales margins. For example, if a product recommendation leads to increased demand for a particular item, the dynamic pricing algorithm can adjust the price to capitalize on this heightened interest, thereby maximizing revenue. Understanding the purchasing behavior of different age groups can inform dynamic pricing strategies. Younger consumers, who are more price-sensitive and tech-savvy, might respond better to flash sales and discounts. Conversely, older consumers, who might prioritize product quality and convenience, could be targeted with stable pricing and loyalty rewards. AI models can segment consumers based on age and tailor dynamic pricing strategies accordingly. AI can analyze consumer income data to adjust pricing strategies dynamically. For higher-income consumers, premium pricing for exclusive products might be more effective, while lower-income segments could be targeted with competitive pricing and discounts. The results emphasize how important income is when making judgments about what to buy suggesting that personalized dynamic pricing can enhance consumer satisfaction and engagement. Dynamic pricing can expand the options and choices available to consumers. By adjusting prices in real-time, e-commerce platforms can manage inventory more effectively and offer a broader range of products at various price points. This aligns with the hypothesis that product recommendations should provide more options and choices, ensuring that consumers find products that meet their expectations and budgets. Dynamic pricing is integral to developing a personalized shopping experience. AI can analyze individual consumer data, including browsing history, past purchases, and price sensitivity, to tailor pricing strategies. Customers are more likely to feel appreciated and understood when they receive personalized pricing, which improves their whole buying experience and encourages repeat business. The study underscores AI's role in not only updating new product launches but also in creating innovative consumer strategies. Dynamic pricing is one such innovation, where AI continuously learns and adapts to market conditions, consumer behavior, and competitive actions. This real-time adjustment capability ensures that pricing strategies remain relevant and effective, keeping consumers engaged and driving sales growth. The study's conclusions demonstrate how AI might improve e-commerce success through product recommendations. Extending this analysis to dynamic pricing optimization reveals a synergistic relationship where both elements (product recommendations and pricing strategies) can be fine-tuned through deep learning and machine learning techniques. By leveraging AI for dynamic pricing, e-commerce platforms can achieve a more responsive, personalized, and profitable approach to online retailing, ultimately improving user engagement and sales.

The objective of this investigation is to investigate how sales, customer satisfaction, and productivity in the e-commerce industry are affected by AI-driven product recommendations. This investigation is particularly relevant in the context of psychology as it delves into how AI influences consumer behavior, decision-making processes, and overall satisfaction. The psychological aspect here revolves around how consumers perceive the efficiency and utility of AI recommendations. When AI systems streamline the shopping experience by providing relevant product suggestions, consumers may feel that their time and effort are saved, leading to increased productivity. This perceived efficiency can enhance the overall shopping experience, reducing cognitive load and decision fatigue. From a psychological perspective, the enhancement of sales through AI recommendations can be linked to consumer trust and the perceived credibility of the recommendations. When consumers trust that the AI understands their preferences and provides accurate suggestions, they are more likely to make purchases. This trust is an important psychological component that has a big impact on purchasing decisions. The improvement in consumer experience through AI recommendations is deeply rooted in psychological satisfaction. When AI accurately predicts and caters to individual preferences, it creates a sense of being understood and valued, which enhances consumer satisfaction. Positive emotional responses to tailored recommendations can lead to increased loyalty and repeat purchases. The study also considers the age of consumers, recognizing that different age groups may have varying levels of comfort and trust in AI technology. Younger consumers, who are generally more tech-savvy, might have a more positive experience with AI recommendations compared to older consumers who might be more skeptical or require more assurance about the technology's benefits. The psychological factor of income influencing purchasing decisions highlights the role of financial security in consumer behavior. Higher-income consumers may have more discretionary spending power and might be more willing to explore and purchase recommended products. This financial confidence can affect how consumers perceive and engage with AI-driven recommendations. AI's ability to offer more options and choices taps into the psychological principle of autonomy and control. When consumers feel they have a wide range of options to choose from, they experience a sense of control over their purchasing decisions, which can enhance satisfaction and reduce decision-making stress. Personalization in AI recommendations addresses the psychological need for individual recognition and personal relevance. Consumers appreciate when their unique preferences are acknowledged, resulting in a more interesting and customized shopping experience. This personalization can create emotional connections and foster brand loyalty. The innovative strategies created by AI, including updating new product launches, can stimulate consumer interest and curiosity. Psychologically, this can lead to increased engagement as consumers are attracted to novel and innovative offerings. The anticipation of new and personalized recommendations can enhance the overall shopping experience and keep consumers returning to the platform. In summary, this study integrates psychological principles to understand how AI-driven product recommendations influence consumer behavior in e-commerce. Through taking into account elements like financial stability, autonomy, trust, contentment, and personalization, the research seeks to offer a thorough grasp of the psychological mechanisms that propel consumer engagement and sales via AI technology.

For practitioners, this study underscores the necessity of integrating AI technologies strategically to enhance consumer experience and drive business growth. By leveraging multi-modal data sources and addressing ethical considerations, businesses can develop innovative and effective AI-driven recommendation systems that cater to diverse consumer needs and preferences. The results also imply that optimizing customer pleasure and engagement requires striking a balance between AI automation and human connection. Overall, the goal of this study is to demonstrate the revolutionary potential of AI in e-commerce while offering a thorough framework for further investigation and real-world implementations.

Theoretical implication

This study on harnessing AI potential in e-commerce for improving user engagement and sales through deep learning-based product recommendations offers significant theoretical implications. It emphasizes how crucial AI is to raising sales and productivity while showcasing AI's ability to improve e-commerce decision-making and business operations. Moreover, the findings emphasize the importance of personalized AI systems in improving consumer experience by providing more options and choices, thereby enhancing satisfaction and engagement. The study also demonstrates how customer behavior in reaction to AI-driven recommendations is influenced by demographic parameters like age and income underscoring the need for tailored approaches to maximize effectiveness. Additionally, the research underscores AI's capability not only to update product recommendations with new launches but also to innovate consumer engagement strategies, contributing to theoretical advancements in AI-driven marketing innovations.

Practical implications

Harnessing AI potential in e-commerce for improving user engagement and sales through deep learning-based product recommendations offers several practical implications. It enhances operational efficiency by automating personalized suggestions, thereby optimizing resource allocation and reducing manual intervention. It boosts sales by improving conversion rates and average order values through more accurate and relevant product recommendations. It enhances customer satisfaction by reducing decision-making fatigue and fostering loyalty through personalized shopping experiences. Additionally, targeted marketing strategies based on consumer segmentation by age and income levels enable more effective promotional campaigns. Moreover, AI-driven recommendations diversify product offerings, exposing consumers to a wider range of products and potentially increasing sales volume. Furthermore, personalized user journeys deepen engagement by delivering relevant content and offers throughout the customer journey, thereby enhancing interaction rates and overall engagement metrics. AI's predictive analytics capabilities drive continuous innovation in consumer strategies, enabling businesses to stay ahead of market trends and meet evolving consumer preferences effectively. These implications underscore how integrating AI into e-commerce operations can yield significant benefits across efficiency, sales growth, customer satisfaction, targeted marketing, product diversity, user engagement, and ongoing innovation.

Conclusion

This study used a quantitative research design to investigate how productivity is affected by AI-driven product recommendations, sales performance, and consumer experience in the e-commerce sector. Conducted among 439 consumers and 356 sellers across various regions of China, the study offered insightful information about how AI technologies are changing the dynamics of online commerce. The results demonstrated how important AI-driven product recommendations are for boosting e-commerce revenues and productivity. By utilizing advanced deep learning algorithms, businesses can effectively tailor product suggestions to individual consumer preferences, thereby improving user engagement and satisfaction. These recommendations were observed to cater to diverse consumer demographics, including different age groups and income brackets, highlighting AI's ability to personalize shopping experiences. Furthermore, AI-powered recommendation systems were found to expand consumer choices and facilitate personalized interactions, enriching overall shopping experiences. Beyond efficiency gains, AI fosters innovation in marketing strategies by enabling real-time adaptation to consumer behavior trends and preferences. This capability optimizes operational processes and enhances the consumer-centric nature of online shopping platforms. As a result, this study highlights the revolutionary potential of AI in modern e-commerce and calls for more research and implementation of advanced AI technologies to sustainably enhance user engagement, sales performance, and operational efficiency in digital commerce contexts. Future research should focus on refining AI algorithms, addressing ethical considerations, and exploring new approaches to integrate multimodal data sources to improve the efficiency and diversity of AI-powered e-commerce recommendations.

Limitations

The study's limitations include potential sampling bias due to purposive sampling from specific e-commerce active regions in China, limiting generalizability. Self-reported data may introduce response biases, and the cross-sectional design prevents establishing causal relationships over time. Measurement scales for variables like consumer experience may lack comprehensive nuance. Technological constraints focused on deep learning-based recommendations without accounting for emerging AI variations or platform-specific implementations. Addressing these limitations in future research would enhance understanding of AI's impact on e-commerce dynamics.

Recommendations for future research

Future research could explore longitudinal studies to establish causal relationships between AI-driven recommendations and e-commerce outcomes over time. Investigating diverse geographical regions and demographic groups would enhance generalizability. Enhanced methodologies integrating a more in-depth understanding of customer attitudes and behavior may be possible with qualitative methods. Exploring advanced AI techniques beyond deep learning, such as reinforcement learning or hybrid models, could optimize recommendation accuracy. Collaborative research with industry partners could validate findings in real-world settings, fostering practical applications and innovations in e-commerce strategies.

Going forward, it is imperative to investigate how recommendation frameworks in AI-driven e-commerce may incorporate multi-modal data sources like text, graphics, and user interactions. Adopting advanced multi-modal learning approaches, particularly deep neural networks capable of processing and interpreting diverse data types simultaneously, holds promise for enhancing the granularity and personalization of product recommendations. This approach can cater more effectively to diverse user preferences and contexts, potentially increasing engagement and satisfaction. Future studies should also focus on developing robust models that fuse and interpret varied signals from user interactions across different modalities such as textual reviews, image interactions, and browsing behaviors to gain deeper insights into user intent and preferences. Context-aware recommendation systems that dynamically adjust recommendations based on real-time user context, including location and time of day, could benefit from incorporating multimodal data to make recommendations more adaptive and responsive. Additionally, rigorous validation and benchmarking studies comparing multi-modal recommendation systems against traditional uni-modal approaches will provide empirical evidence of their effectiveness and added value in enhancing recommendation quality. By exploring these avenues, future research can propel advancements in AI-driven product recommendations, ultimately delivering more sophisticated and adaptive systems that better serve the diverse needs of consumers in e-commerce environments.

Acknowledgements The Science and Technology Plan Project of Nantong Science and Technology Bureau (in 2015):The Research of the E-Commerce Development in "Internet +" of Agricultural Products in Nantong.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability Not applicable.

Declarations

Informed consent Informed consent was obtained from all individual participants included in the study.

Human and animal rights This article does not contain any studies with human or animal subjects performed by any of the authors.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare that they have no conflict of interest.

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